

# Notebook

June 20, 2025

```
[ ]: # Import Libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.metrics import (accuracy_score, confusion_matrix,
    ↪classification_report,
                                roc_auc_score, roc_curve, precision_recall_curve)
from sklearn.preprocessing import StandardScaler, LabelEncoder
```

```
[ ]: # Load and Inspect Data

df = pd.read_csv("student_depression_dataset.csv")

print(df.head())
print(df.info())
print(df.describe(include='all'))
print("\nMissing values per column:\n", df.isnull().sum())
```

	id	Gender	Age	City	Profession	Academic Pressure	\
0	2	Male	33.0	Visakhapatnam	Student	5.0	
1	8	Female	24.0	Bangalore	Student	2.0	
2	26	Male	31.0	Srinagar	Student	3.0	
3	30	Female	28.0	Varanasi	Student	3.0	
4	32	Female	25.0	Jaipur	Student	4.0	

	Work Pressure	CGPA	Study Satisfaction	Job Satisfaction	\
0	0.0	8.97	2.0	0.0	
1	0.0	5.90	5.0	0.0	
2	0.0	7.03	5.0	0.0	
3	0.0	5.59	2.0	0.0	
4	0.0	8.13	3.0	0.0	

	Sleep Duration	Dietary Habits	Degree \
0	'5-6 hours'	Healthy	B.Pharm
1	'5-6 hours'	Moderate	BSc
2	'Less than 5 hours'	Healthy	BA
3	'7-8 hours'	Moderate	BCA
4	'5-6 hours'	Moderate	M.Tech

	Have you ever had suicidal thoughts ?	Work/Study Hours	Financial Stress \
0	Yes	3.0	1.0
1	No	3.0	2.0
2	No	9.0	1.0
3	Yes	4.0	5.0
4	Yes	1.0	1.0

	Family History of Mental Illness	Depression
0	No	1
1	Yes	0
2	Yes	0
3	Yes	1
4	No	0

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 27901 entries, 0 to 27900

Data columns (total 18 columns):

#	Column	Non-Null Count	Dtype
0	id	27901 non-null	int64
1	Gender	27901 non-null	object
2	Age	27901 non-null	float64
3	City	27901 non-null	object
4	Profession	27901 non-null	object
5	Academic Pressure	27901 non-null	float64
6	Work Pressure	27901 non-null	float64
7	CGPA	27901 non-null	float64
8	Study Satisfaction	27901 non-null	float64
9	Job Satisfaction	27901 non-null	float64
10	Sleep Duration	27901 non-null	object
11	Dietary Habits	27901 non-null	object
12	Degree	27901 non-null	object
13	Have you ever had suicidal thoughts ?	27901 non-null	object
14	Work/Study Hours	27901 non-null	float64
15	Financial Stress	27901 non-null	object
16	Family History of Mental Illness	27901 non-null	object
17	Depression	27901 non-null	int64

dtypes: float64(7), int64(2), object(9)

memory usage: 3.8+ MB

None

	id	Gender	Age	City	Profession \
count	27901.000000	27901	27901.000000	27901	27901

unique	NaN	2	NaN	52	14
top	NaN	Male	NaN	Kalyan	Student
freq	NaN	15547	NaN	1570	27870
mean	70442.149421	NaN	25.822300	NaN	NaN
std	40641.175216	NaN	4.905687	NaN	NaN
min	2.000000	NaN	18.000000	NaN	NaN
25%	35039.000000	NaN	21.000000	NaN	NaN
50%	70684.000000	NaN	25.000000	NaN	NaN
75%	105818.000000	NaN	30.000000	NaN	NaN
max	140699.000000	NaN	59.000000	NaN	NaN

	Academic Pressure	Work Pressure	CGPA	Study Satisfaction \
count	27901.000000	27901.000000	27901.000000	27901.000000
unique	NaN	NaN	NaN	NaN
top	NaN	NaN	NaN	NaN
freq	NaN	NaN	NaN	NaN
mean	3.141214	0.000430	7.656104	2.943837
std	1.381465	0.043992	1.470707	1.361148
min	0.000000	0.000000	0.000000	0.000000
25%	2.000000	0.000000	6.290000	2.000000
50%	3.000000	0.000000	7.770000	3.000000
75%	4.000000	0.000000	8.920000	4.000000
max	5.000000	5.000000	10.000000	5.000000

	Job Satisfaction	Sleep Duration	Dietary Habits	Degree \
count	27901.000000	27901	27901	27901
unique	NaN	5	4	28
top	NaN	'Less than 5 hours'	Unhealthy	'Class 12'
freq	NaN	8310	10317	6080
mean	0.000681	NaN	NaN	NaN
std	0.044394	NaN	NaN	NaN
min	0.000000	NaN	NaN	NaN
25%	0.000000	NaN	NaN	NaN
50%	0.000000	NaN	NaN	NaN
75%	0.000000	NaN	NaN	NaN
max	4.000000	NaN	NaN	NaN

	Have you ever had suicidal thoughts ?	Work/Study Hours \
count	27901	27901.000000
unique	2	NaN
top	Yes	NaN
freq	17656	NaN
mean	NaN	7.156984
std	NaN	3.707642
min	NaN	0.000000
25%	NaN	4.000000
50%	NaN	8.000000
75%	NaN	10.000000

max		NaN	12.000000
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	Financial Stress	Family History of Mental Illness	Depression
count	27901	27901	27901.000000
unique	6	2	NaN
top	5.0	No	NaN
freq	6715	14398	NaN
mean	NaN	NaN	0.585499
std	NaN	NaN	0.492645
min	NaN	NaN	0.000000
25%	NaN	NaN	0.000000
50%	NaN	NaN	1.000000
75%	NaN	NaN	1.000000
max	NaN	NaN	1.000000

Missing values per column:

id	0
Gender	0
Age	0
City	0
Profession	0
Academic Pressure	0
Work Pressure	0
CGPA	0
Study Satisfaction	0
Job Satisfaction	0
Sleep Duration	0
Dietary Habits	0
Degree	0
Have you ever had suicidal thoughts ?	0
Work/Study Hours	0
Financial Stress	0
Family History of Mental Illness	0
Depression	0
dtype: int64	

```
[ ]: # Target/Features Split & Basic Insights

target_col = 'Depression'
target = df[target_col]
features = df.drop([target_col], axis=1)
num_cols = features.select_dtypes(include=[np.number]).columns.tolist()

print("\n==== BASIC INSIGHTS =====")
print(f"Number of students: {df.shape[0]}")
print(f"Number of features: {df.shape[1]}")
print(f"Unique values in target column: {df[target_col].unique()}")
```

```
print("\nTarget value counts:\n", target.value_counts())
```

===== BASIC INSIGHTS =====

Number of students: 27901

Number of features: 18

Unique values in target column: [1 0]

Target value counts:

Depression

1 16336

0 11565

Name: count, dtype: int64

```
[5]: # Gender and other categorical breakdowns if present
if 'Gender' in df.columns:
    print("\n===== Gender Breakdown =====\n", df['Gender'].value_counts())
    plt.figure(figsize=(5,3))
    sns.countplot(x='Gender', data=df, hue=target_col)
    plt.title('Depression by Gender')
    plt.show()
```

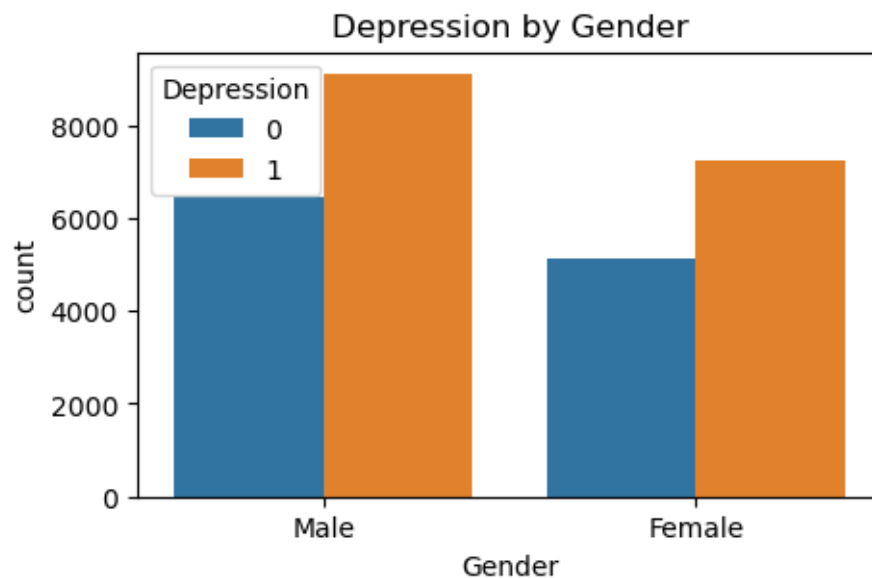
===== Gender Breakdown =====

Gender

Male 15547

Female 12354

Name: count, dtype: int64



```
[6]: # Group means for key variables
print("\n==== Mean values by Depression ==== \n")
print(df.groupby(target_col).mean(numeric_only=True))
```

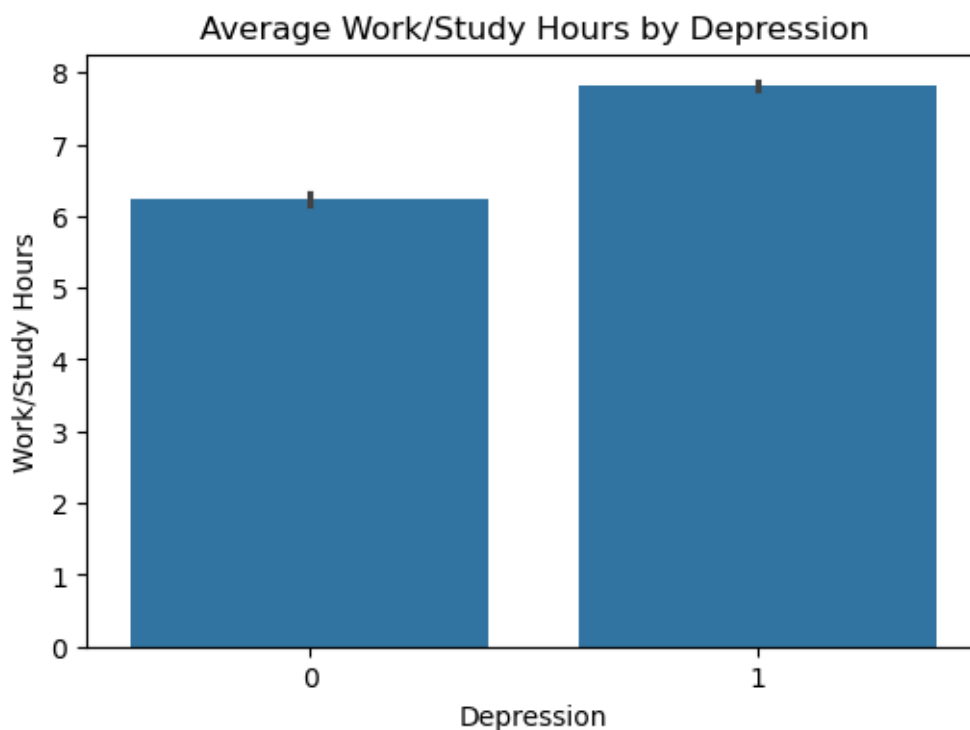
==== Mean values by Depression ====

	id	Age	Academic Pressure	Work Pressure	\
Depression					
0	70397.561089	27.142412	2.361608	0.000605	
1	70473.715536	24.887733	3.693132	0.000306	

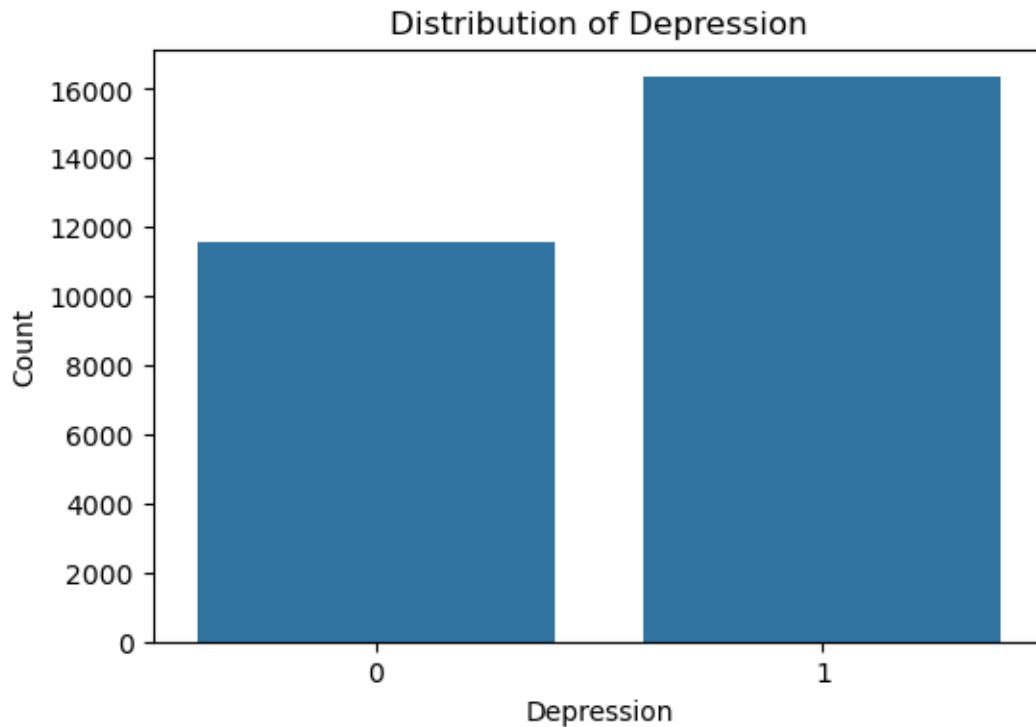
	CGPA	Study Satisfaction	Job Satisfaction	Work/Study Hours
Depression				
0	7.617282	3.215564	0.000865	6.237959
1	7.683588	2.751469	0.000551	7.807603

```
[7]: # Bar plot of average study hours (if present) by depression
if 'Work/Study Hours' in df.columns:
    plt.figure(figsize=(6,4))
    sns.barplot(x=target_col, y='Work/Study Hours', data=df)
    plt.title('Average Work/Study Hours by Depression')
    plt.show()
```

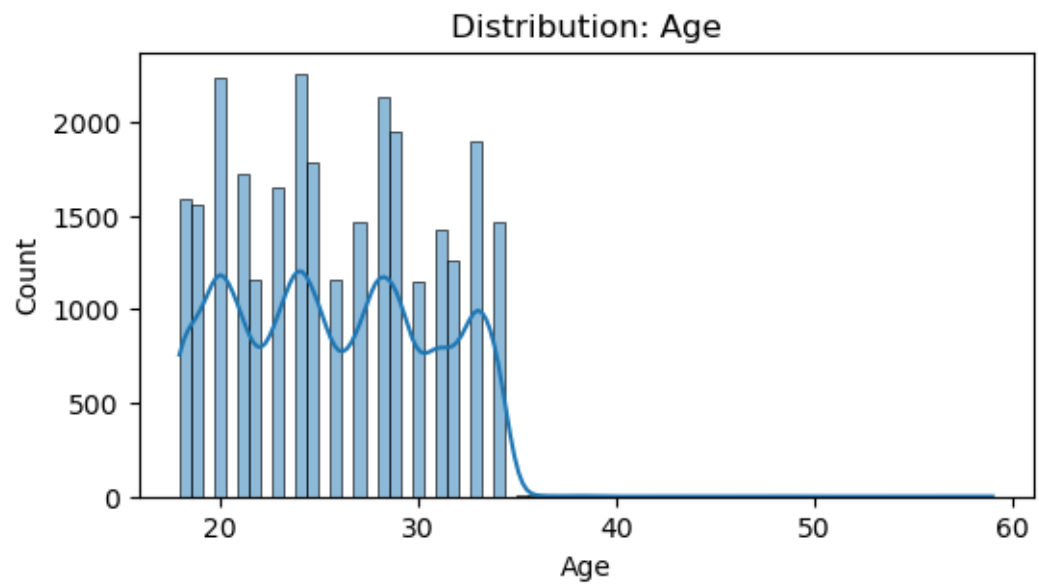
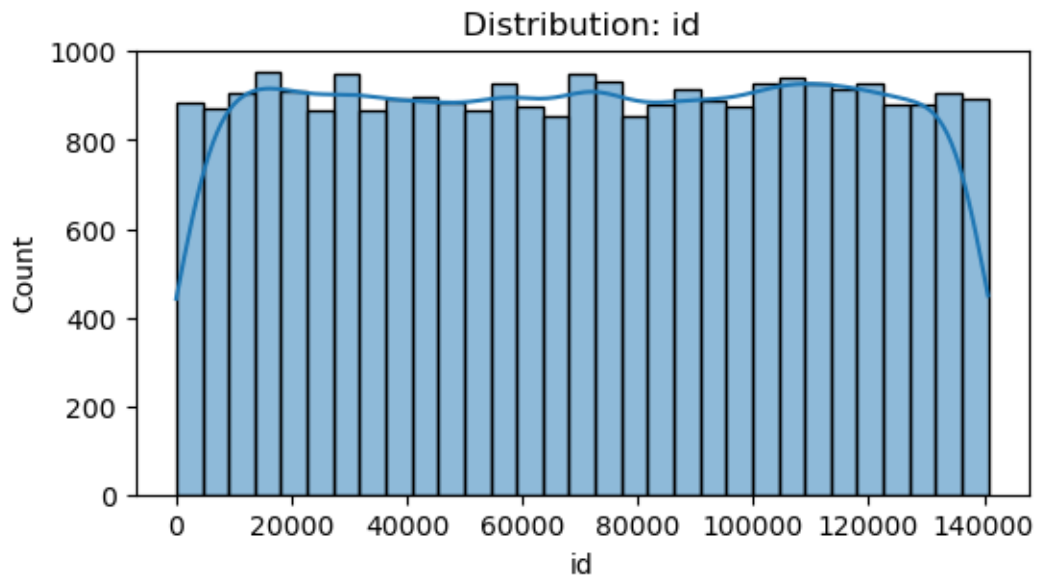


## 1 EDA Visualizations

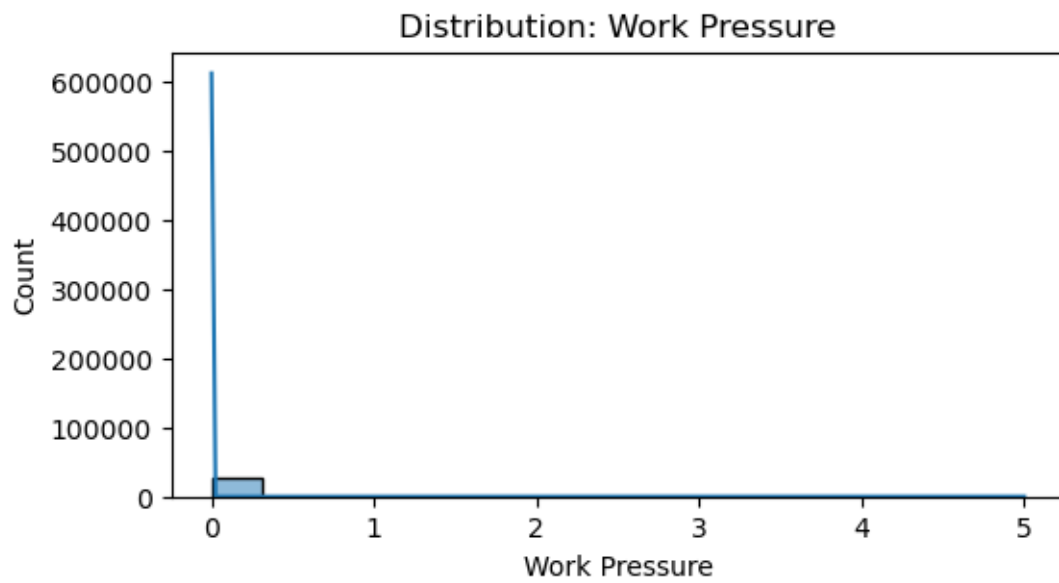
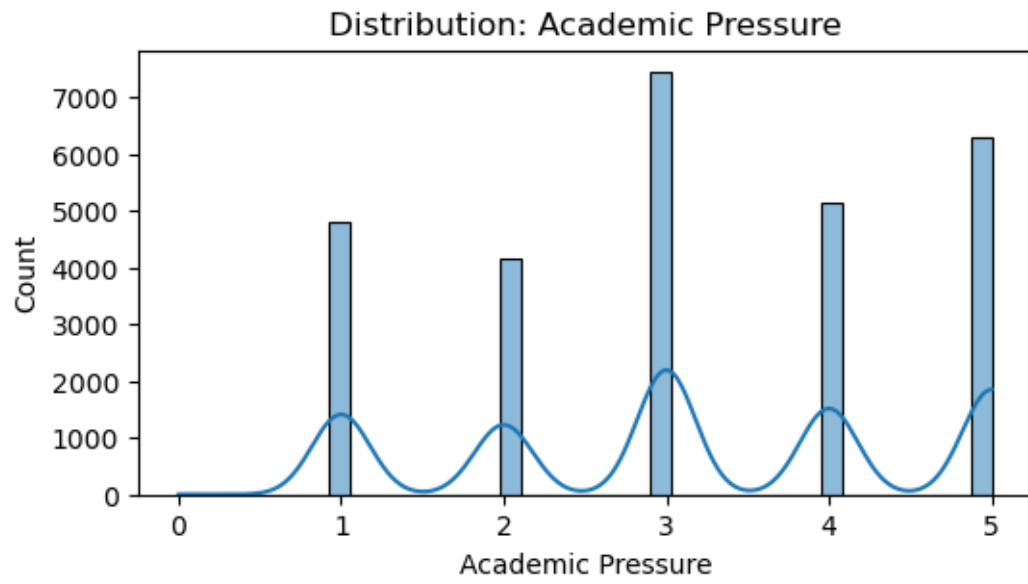
```
[8]: # Visualize target distribution
plt.figure(figsize=(6, 4))
sns.countplot(x=target_col, data=df)
plt.title('Distribution of Depression')
plt.xlabel('Depression')
plt.ylabel('Count')
plt.show()
```

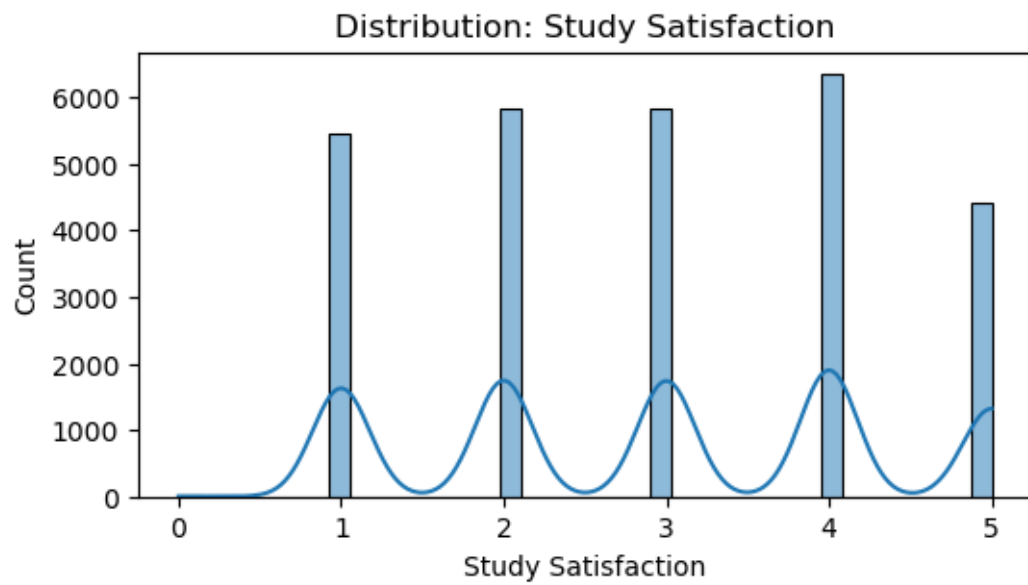
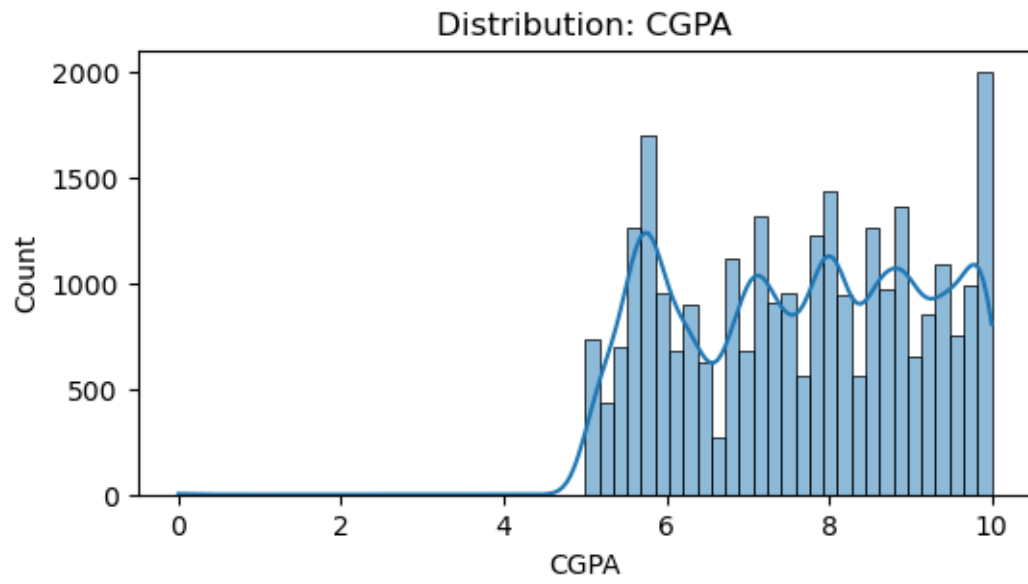


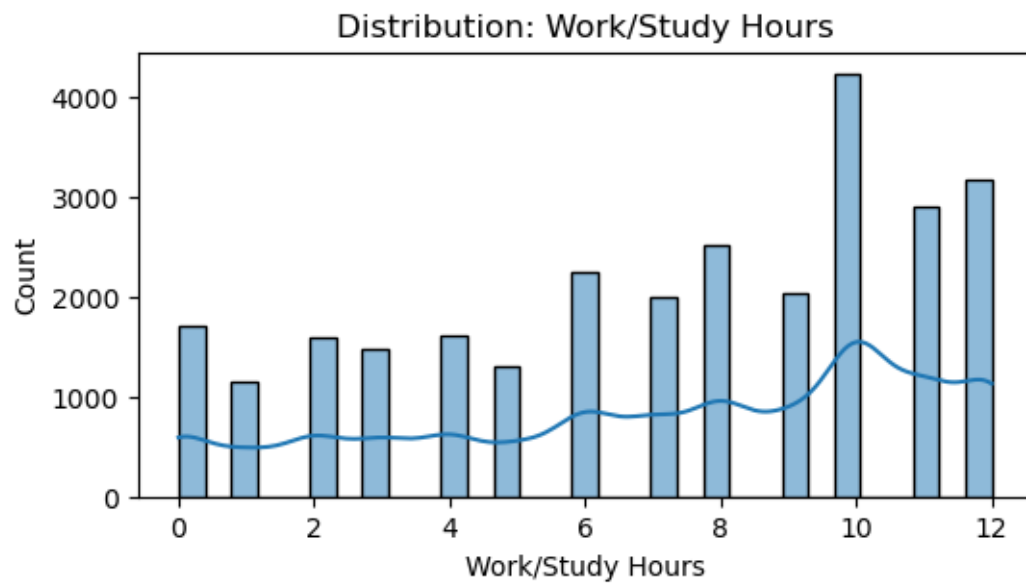
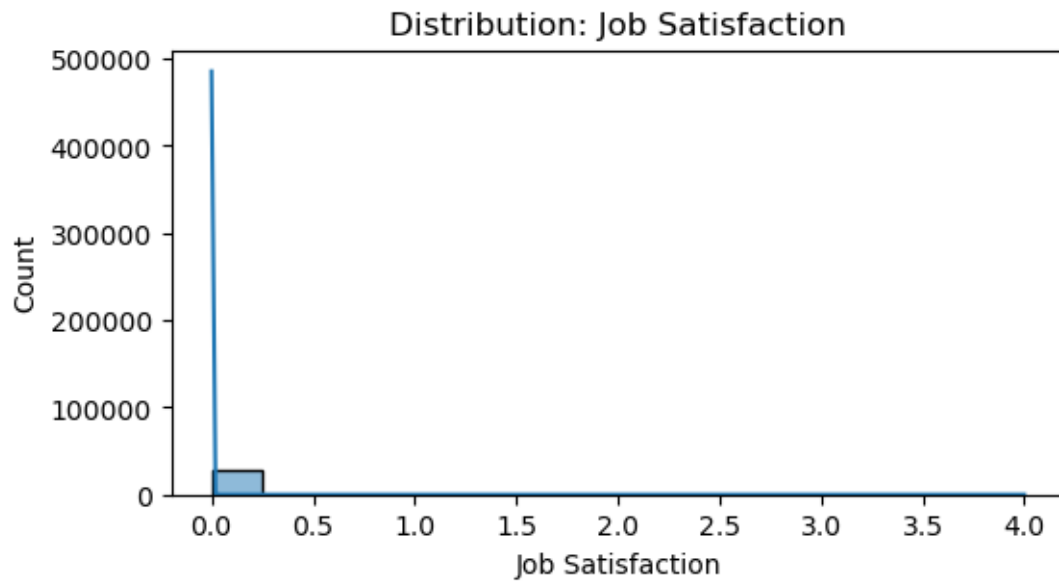
```
[9]: # Histograms for numerical features
for col in num_cols:
    plt.figure(figsize=(6, 3))
    sns.histplot(df[col], kde=True)
    plt.title(f'Distribution: {col}')
    plt.show()
```





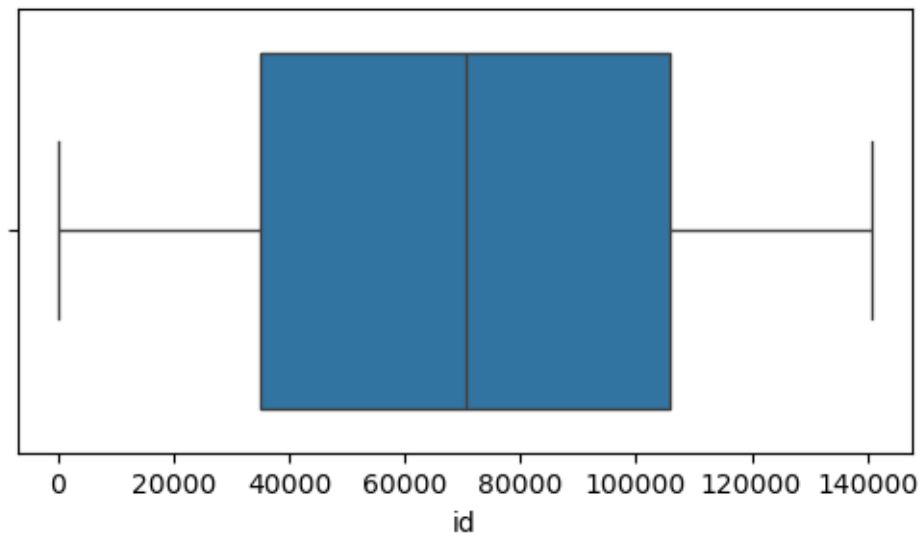




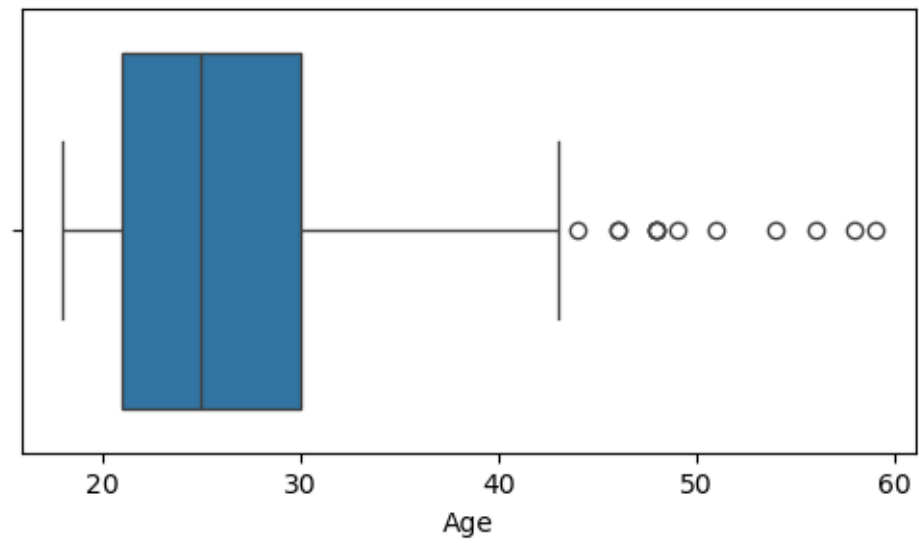


```
[10]: # Boxplots for outlier inspection
for col in num_cols:
    plt.figure(figsize=(6, 3))
    sns.boxplot(x=df[col])
    plt.title(f'Boxplot: {col}')
    plt.show()
```

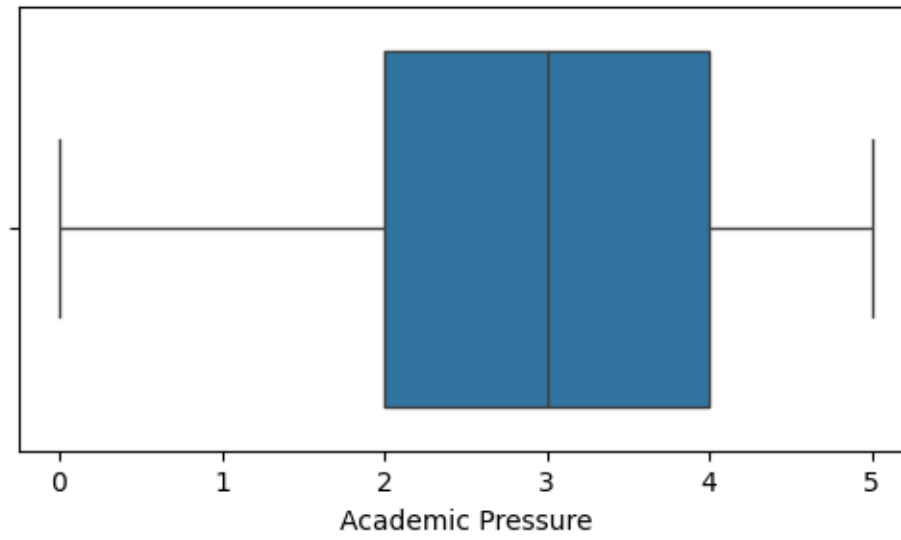
Boxplot: id



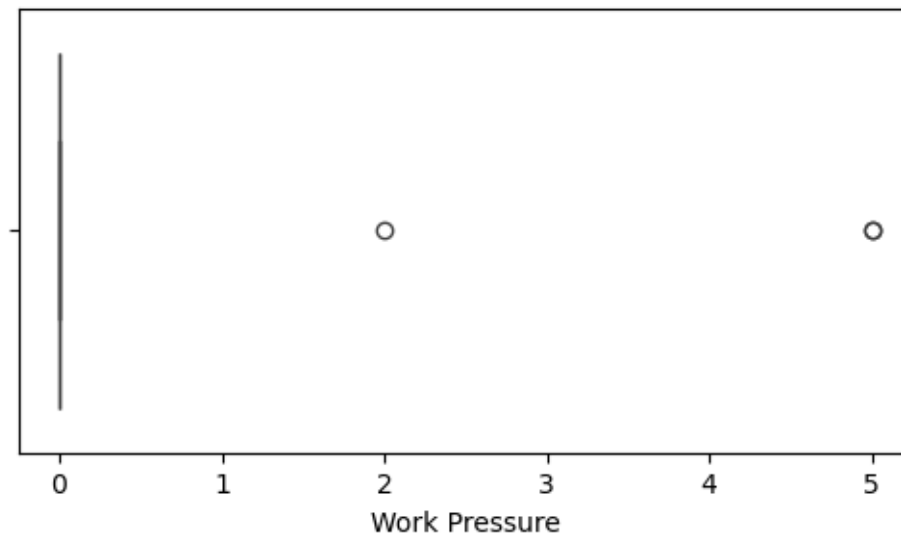
Boxplot: Age



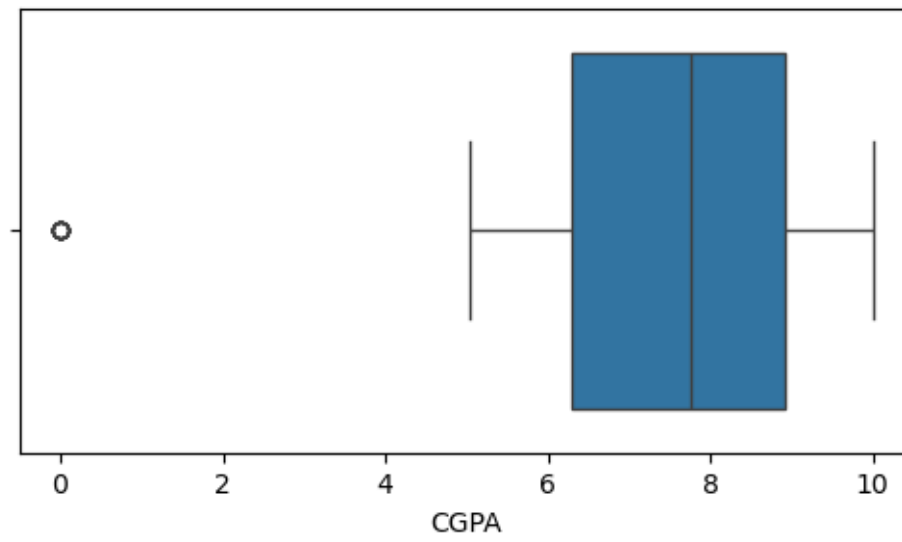
Boxplot: Academic Pressure



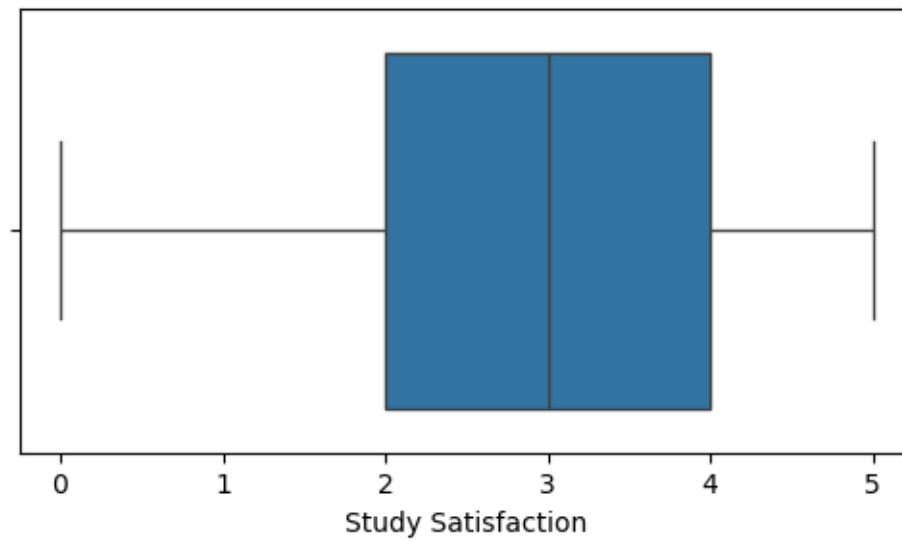
Boxplot: Work Pressure

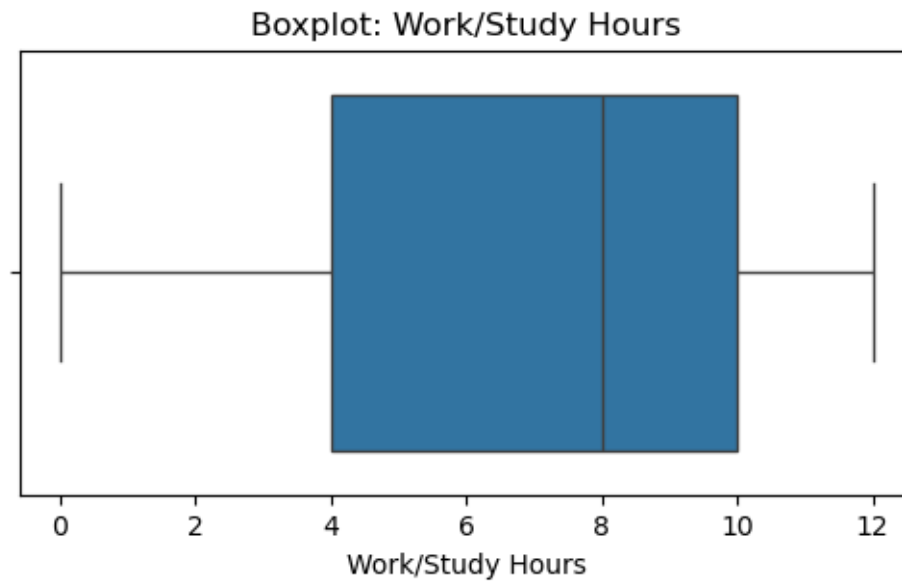
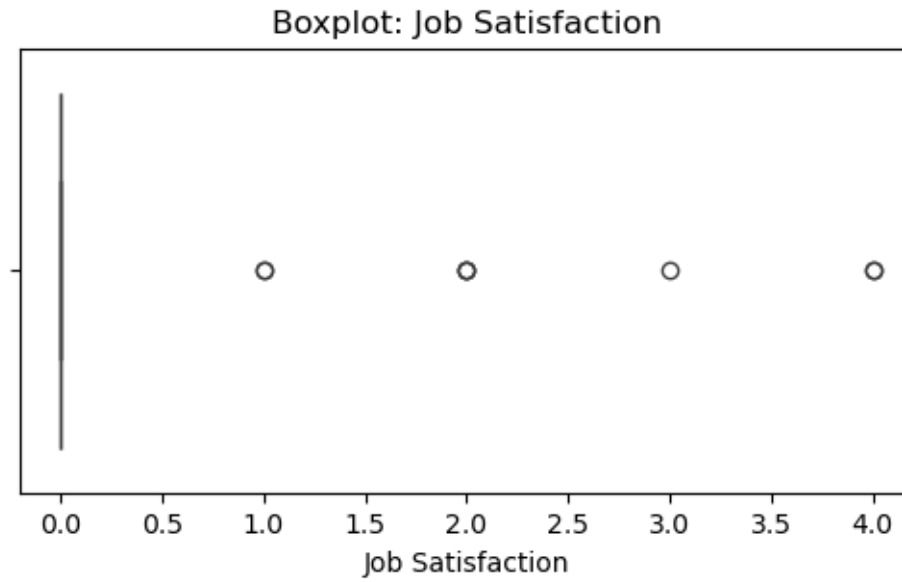


Boxplot: CGPA

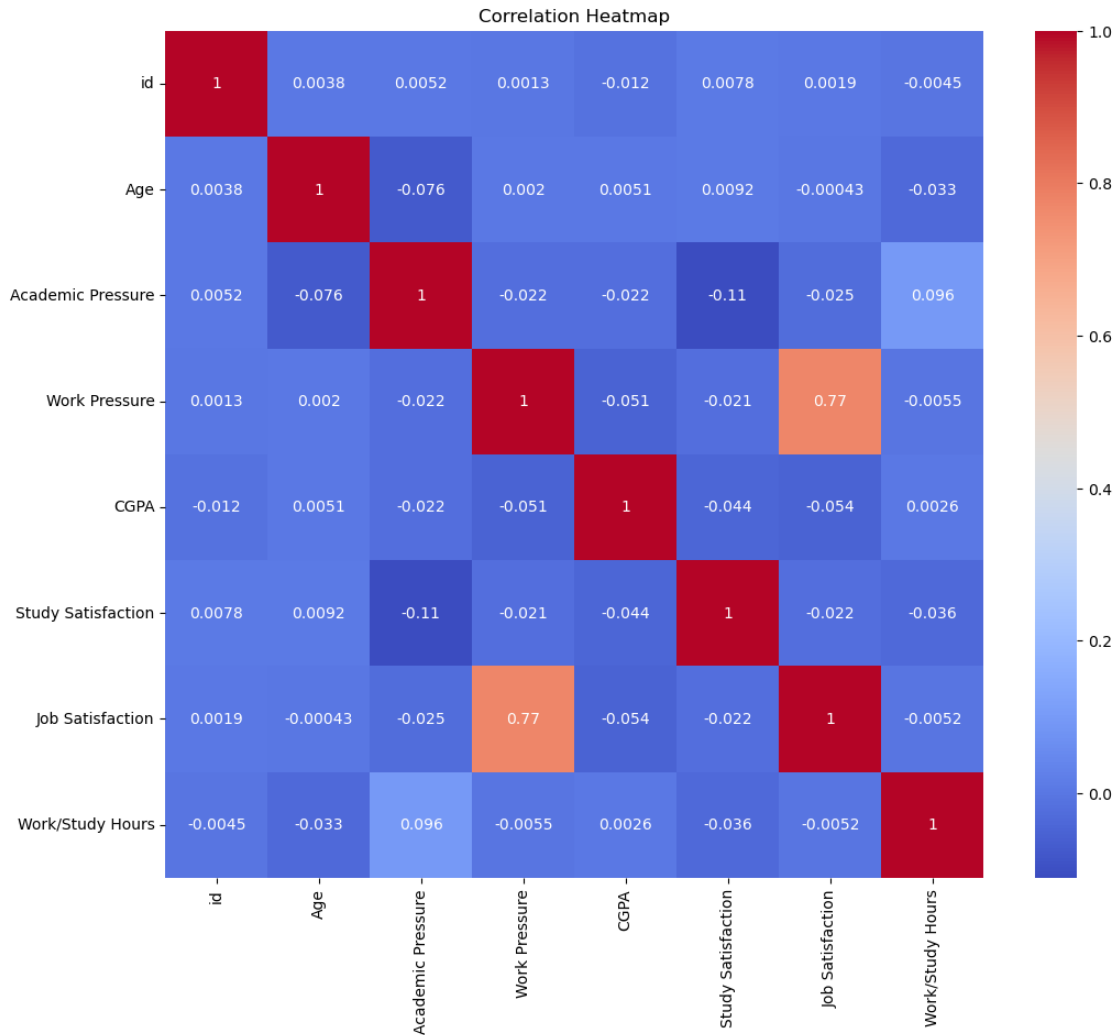


Boxplot: Study Satisfaction





```
[11]: # Correlation heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(df[num_cols].corr(), annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```



## 2 Data Cleaning & Preprocessing

```
[ ]: # Fills missing numerics with median (should be none)
features[num_cols] = features[num_cols].fillna(features[num_cols].median())

# Fills missing categoricals with mode (should be none)
cat_cols = features.select_dtypes(include=['object']).columns
features[cat_cols] = features[cat_cols].fillna(features[cat_cols].mode().
    ↪iloc[0])

# Encode categorical variables
le = LabelEncoder()
for col in cat_cols:
    features[col] = le.fit_transform(features[col].astype(str))
```



```
print("\nAfter encoding, features shape:", features.shape)
print("Sample after encoding:\n", features.head())
```

After encoding, features shape: (27901, 17)

Sample after encoding:

	id	Gender	Age	City	Profession	Academic Pressure	Work Pressure	CGPA
0	2	1	33.0	51	12	5.0	0.0	8.97
1	8	0	24.0	5	12	2.0	0.0	5.90
2	26	1	31.0	44	12	3.0	0.0	7.03
3	30	0	28.0	49	12	3.0	0.0	5.59
4	32	0	25.0	18	12	4.0	0.0	8.13

	Study Satisfaction	Job Satisfaction	Sleep Duration	Dietary Habits
0	2.0	0.0	0	0
1	5.0	0.0	0	1
2	5.0	0.0	2	0
3	2.0	0.0	1	1
4	3.0	0.0	0	1

	Degree	Have you ever had suicidal thoughts ?	Work/Study Hours
0	4	1	3.0
1	11	0	3.0
2	6	0	9.0
3	8	1	4.0
4	17	1	1.0

	Financial Stress	Family History of Mental Illness
0	0	0
1	1	1
2	0	1
3	4	1
4	0	0

[13]: # Train/Test Split and Scaling

```
scaler = StandardScaler()
features_scaled = scaler.fit_transform(features)

X_train, X_test, y_train, y_test = train_test_split(
    features_scaled, target, test_size=0.2, random_state=42, stratify=target
)
print("Train class balance:\n", y_train.value_counts())
print("Test class balance:\n", y_test.value_counts())
```

Train class balance:

```

Depression
1    13068
0     9252
Name: count, dtype: int64
Test class balance:
Depression
1     3268
0     2313
Name: count, dtype: int64

```

### 3 Modeling & Evaluation

```

[14]: # Logistic Regression
logreg = LogisticRegression(max_iter=1000)
logreg.fit(X_train, y_train)
y_pred_logreg = logreg.predict(X_test)
print("\nLogistic Regression Classification Report:\n",
      ↪classification_report(y_test, y_pred_logreg))

```

```

Logistic Regression Classification Report:

```

	precision	recall	f1-score	support
0	0.82	0.79	0.81	2313
1	0.86	0.88	0.87	3268
accuracy			0.84	5581
macro avg	0.84	0.84	0.84	5581
weighted avg	0.84	0.84	0.84	5581

```

[15]: # Decision Tree with GridSearchCV
dt_param_grid = {'max_depth': [None, 5, 10, 15], 'min_samples_split': [2, 5,
      ↪10]}
dt_grid = GridSearchCV(DecisionTreeClassifier(random_state=42), dt_param_grid,
      ↪cv=5)
dt_grid.fit(X_train, y_train)
y_pred_dt = dt_grid.predict(X_test)
print("\nDecision Tree Best Params:", dt_grid.best_params_)
print("Decision Tree Classification Report:\n", classification_report(y_test,
      ↪y_pred_dt))

```

```

Decision Tree Best Params: {'max_depth': 5, 'min_samples_split': 2}
Decision Tree Classification Report:

```

	precision	recall	f1-score	support
0	0.80	0.76	0.78	2313

1	0.84	0.86	0.85	3268
accuracy			0.82	5581
macro avg	0.82	0.81	0.81	5581
weighted avg	0.82	0.82	0.82	5581

```
[16]: # Random Forest with GridSearchCV
rf_param_grid = {'n_estimators': [50, 100, 200], 'max_depth': [None, 10, 20],
    ↪ 'min_samples_split': [2, 5, 10]}
rf_grid = GridSearchCV(RandomForestClassifier(random_state=42), rf_param_grid,
    ↪ cv=5)
rf_grid.fit(X_train, y_train)
y_pred_rf = rf_grid.predict(X_test)
print("\nRandom Forest Best Params:", rf_grid.best_params_)
print("Random Forest Classification Report:\n", classification_report(y_test,
    ↪ y_pred_rf))
```

Random Forest Best Params: {'max\_depth': 20, 'min\_samples\_split': 10, 'n\_estimators': 200}

Random Forest Classification Report:

	precision	recall	f1-score	support
0	0.82	0.78	0.80	2313
1	0.85	0.88	0.86	3268
accuracy			0.84	5581
macro avg	0.84	0.83	0.83	5581
weighted avg	0.84	0.84	0.84	5581

```
[17]: # Gradient Boosting
gb = GradientBoostingClassifier(random_state=42)
gb.fit(X_train, y_train)
y_pred_gb = gb.predict(X_test)
print("\nGradient Boosting Classification Report:\n",
    ↪ classification_report(y_test, y_pred_gb))
```

Gradient Boosting Classification Report:

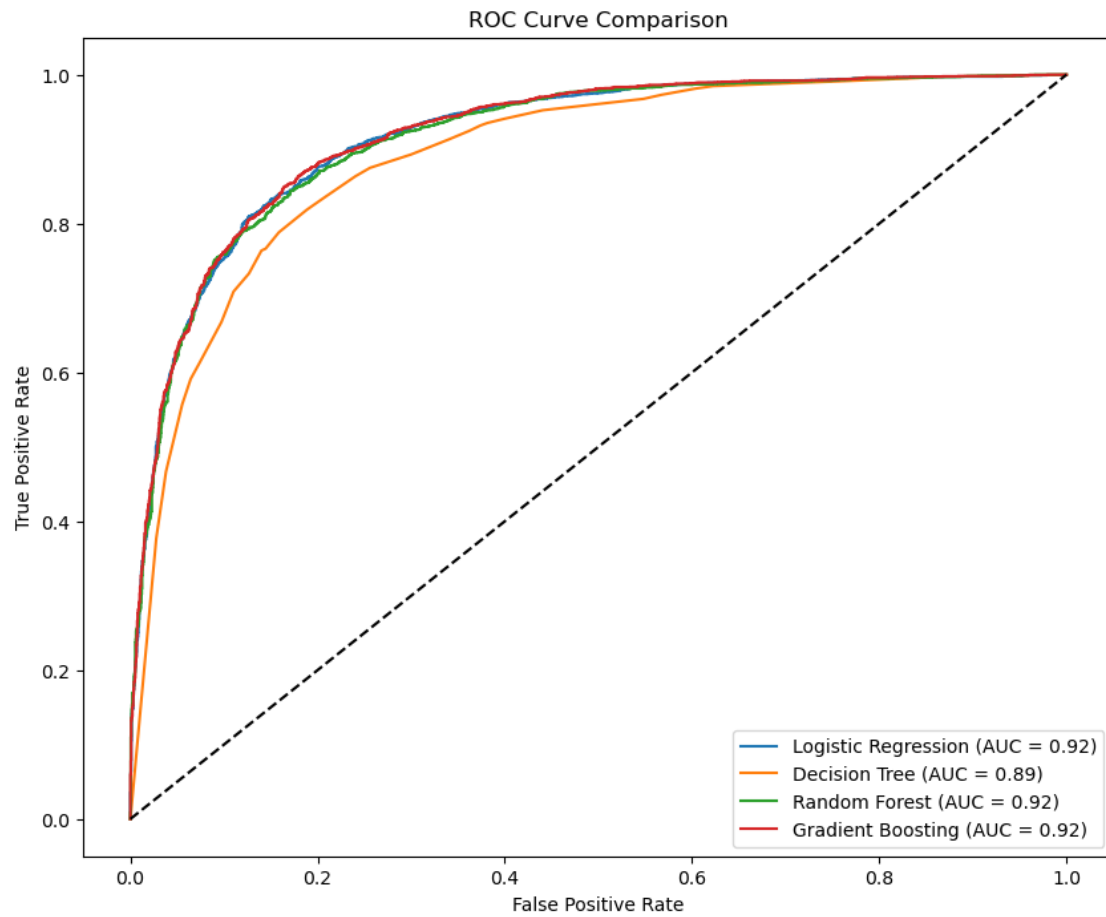
	precision	recall	f1-score	support
0	0.83	0.79	0.81	2313
1	0.86	0.88	0.87	3268
accuracy			0.85	5581
macro avg	0.84	0.84	0.84	5581

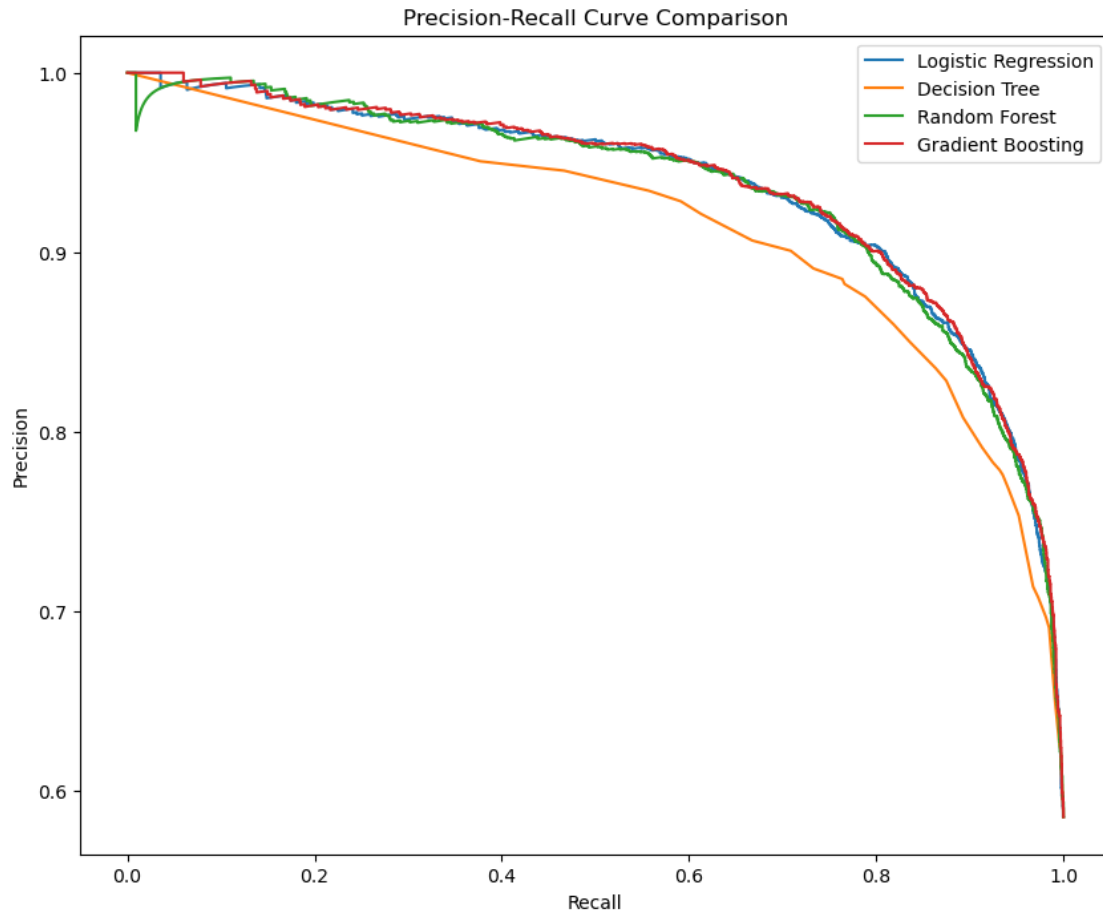
weighted avg	0.85	0.85	0.85	5581
--------------	------	------	------	------

```
[18]: # ROC and Precision-Recall Curves

plt.figure(figsize=(10, 8))
for model, name in zip([logreg, dt_grid, rf_grid, gb],
                        ['Logistic Regression', 'Decision Tree', 'Random Forest', 'Gradient Boosting']):
    y_pred_prob = model.predict_proba(X_test)[: , 1]
    fpr, tpr, _ = roc_curve(y_test, y_pred_prob)
    auc = roc_auc_score(y_test, y_pred_prob)
    plt.plot(fpr, tpr, label=f'{name} (AUC = {auc:.2f})')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate'); plt.ylabel('True Positive Rate')
plt.title('ROC Curve Comparison')
plt.legend(loc='lower right')
plt.show()

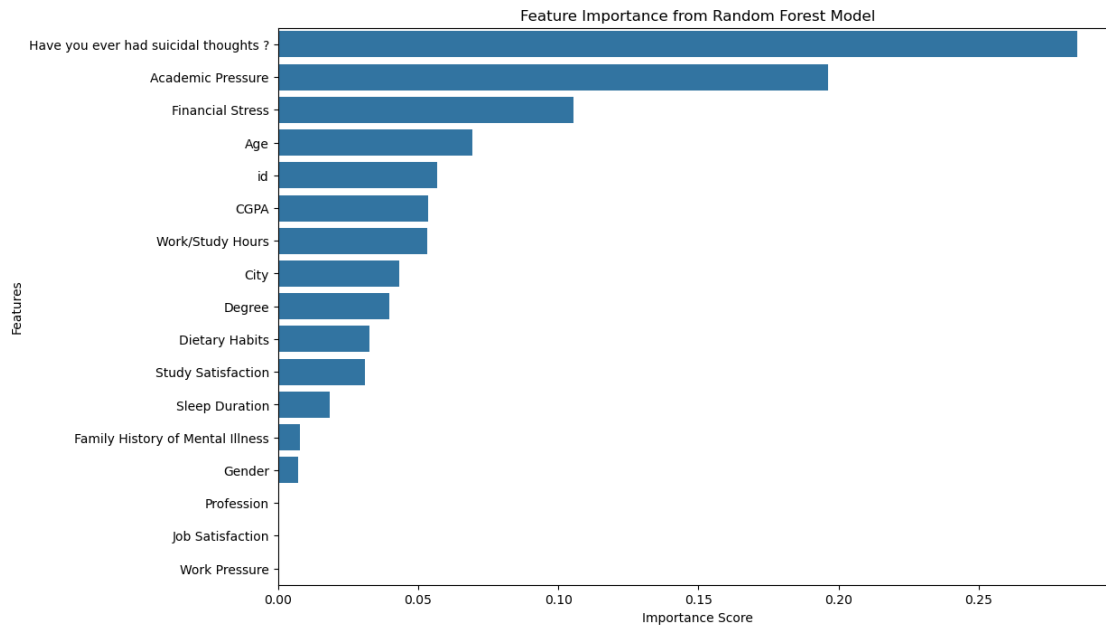
plt.figure(figsize=(10, 8))
for model, name in zip([logreg, dt_grid, rf_grid, gb],
                        ['Logistic Regression', 'Decision Tree', 'Random Forest', 'Gradient Boosting']):
    y_pred_prob = model.predict_proba(X_test)[: , 1]
    precision, recall, _ = precision_recall_curve(y_test, y_pred_prob)
    plt.plot(recall, precision, label=f'{name}')
plt.xlabel('Recall'); plt.ylabel('Precision')
plt.title('Precision-Recall Curve Comparison')
plt.legend(loc='best')
plt.show()
```





```
[19]: # 9. Feature Importance (Random Forest)

importance = rf_grid.best_estimator_.feature_importances_
indices = np.argsort(importance)[::-1]
plt.figure(figsize=(12, 8))
sns.barplot(x=importance[indices], y=features.columns[indices])
plt.title('Feature Importance from Random Forest Model')
plt.xlabel('Importance Score')
plt.ylabel('Features')
plt.show()
```

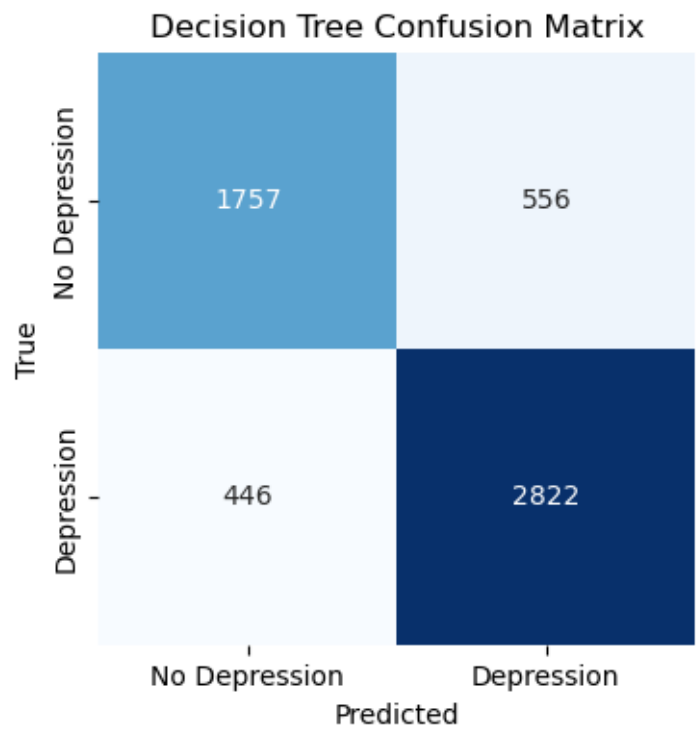
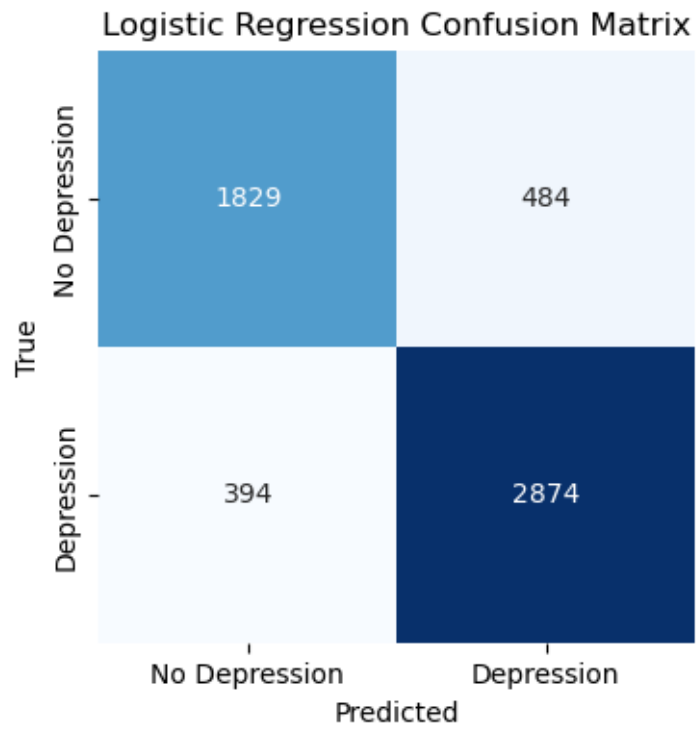


[20]: # 10. Confusion Matrices

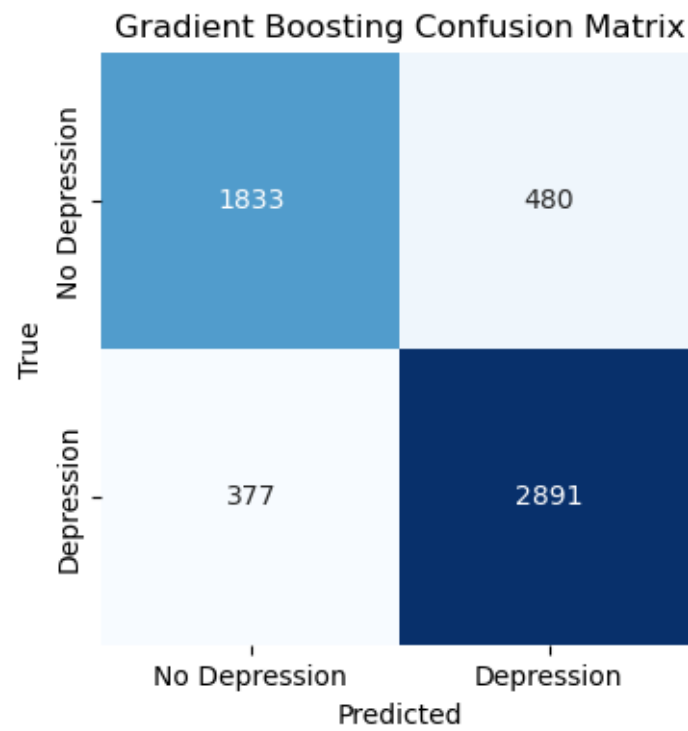
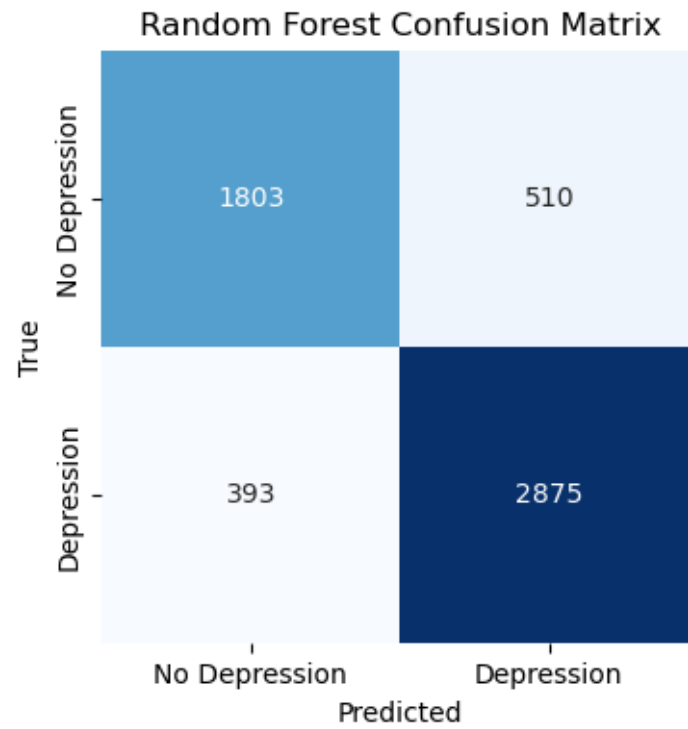
```
def plot_cm(cm, classes, title):
    plt.figure(figsize=(4,4))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False,
                xticklabels=classes, yticklabels=classes)
    plt.title(title)
    plt.xlabel('Predicted')
    plt.ylabel('True')
    plt.show()

models = [logreg, dt_grid, rf_grid, gb]
model_names = ['Logistic Regression', 'Decision Tree', 'Random Forest',
               ↪ 'Gradient Boosting']
preds = [y_pred_logreg, y_pred_dt, y_pred_rf, y_pred_gb]

for name, model, pred in zip(model_names, models, preds):
    cm = confusion_matrix(y_test, pred)
    plot_cm(cm, classes=['No Depression', 'Depression'], title=f'{name}
    ↪ Confusion Matrix')
```







```
[21]: # 11. Accuracy Summary
```

```
print("\n===== FINAL MODEL COMPARISON (ACCURACY) =====")
for name, pred in zip(model_names, preds):
    print(f"{name}: {accuracy_score(y_test, pred):.3f}")
```

```
===== FINAL MODEL COMPARISON (ACCURACY) =====
Logistic Regression: 0.843
Decision Tree: 0.820
Random Forest: 0.838
Gradient Boosting: 0.846
```

```
[ ]: # Reconstructing the dataframe
```

```
X_train, X_test, y_train, y_test = train_test_split(
    features, target, test_size=0.2, random_state=42, stratify=target
)

# Standardize (made sure to keep as DataFrame)
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_train_scaled = pd.DataFrame(scaler.fit_transform(X_train), columns=features.
    ↪columns, index=X_train.index)
X_test_scaled = pd.DataFrame(scaler.transform(X_test), columns=features.
    ↪columns, index=X_test.index)

# Ensuring X_test_scaled is a DataFrame
# shap_values is a list of two arrays: one for each class
print(type(shap_values))
print(len(shap_values))
print(shap_values[0].shape)
print(shap_values[1].shape)
```

```
<class 'numpy.ndarray'>
5581
(17, 2)
(17, 2)
```

```
[31]: # 12. SHAP Explainability (Random Forest)
```

```
import shap

explainer = shap.TreeExplainer(rf_grid.best_estimator_)
shap_values = explainer.shap_values(X_test_scaled)

# If 3D array, take positive class only
if len(shap_values.shape) == 3 and shap_values.shape[2] == 2:
    shap_values_pos = shap_values[:, :, 1]
```

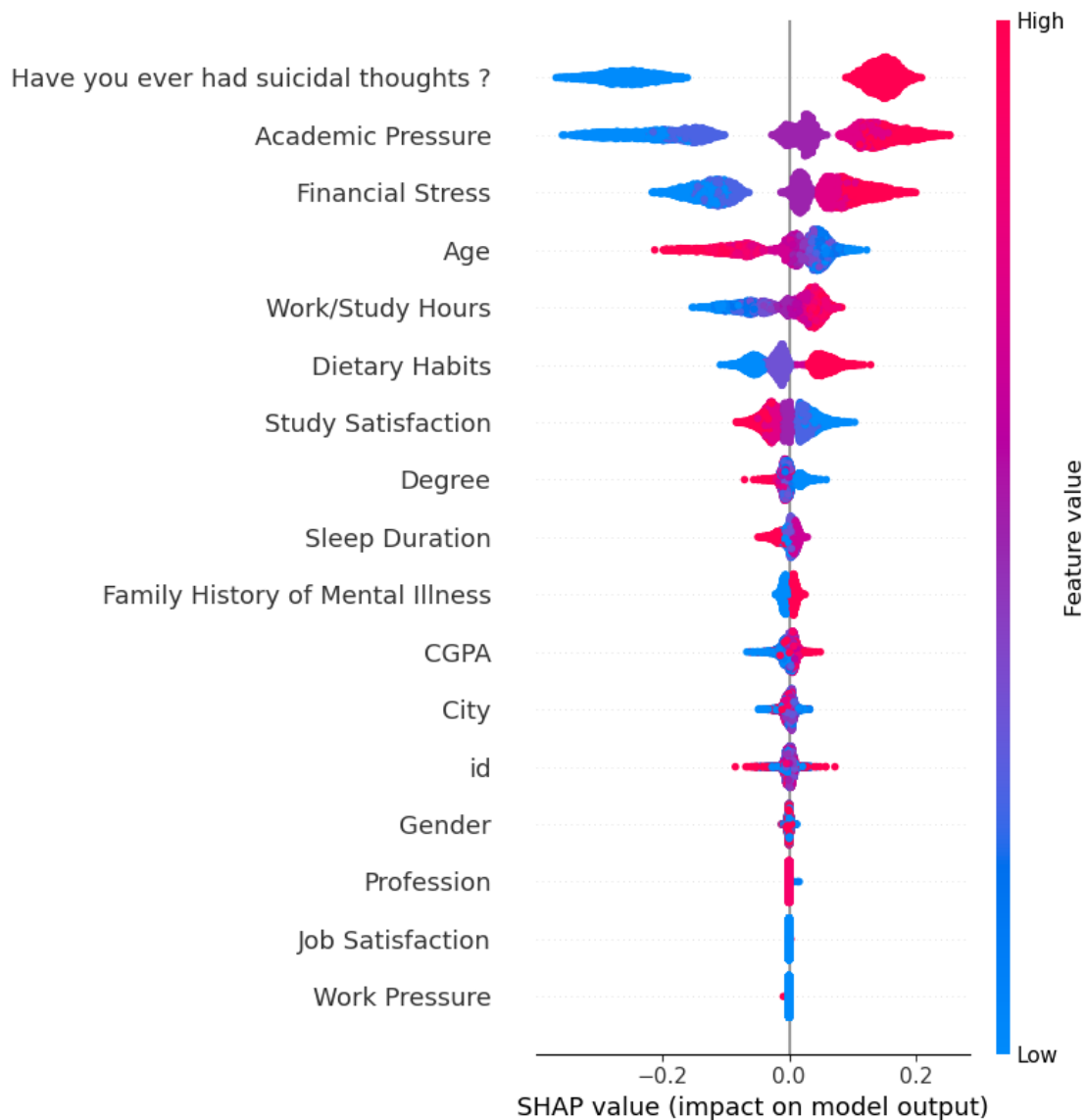
```

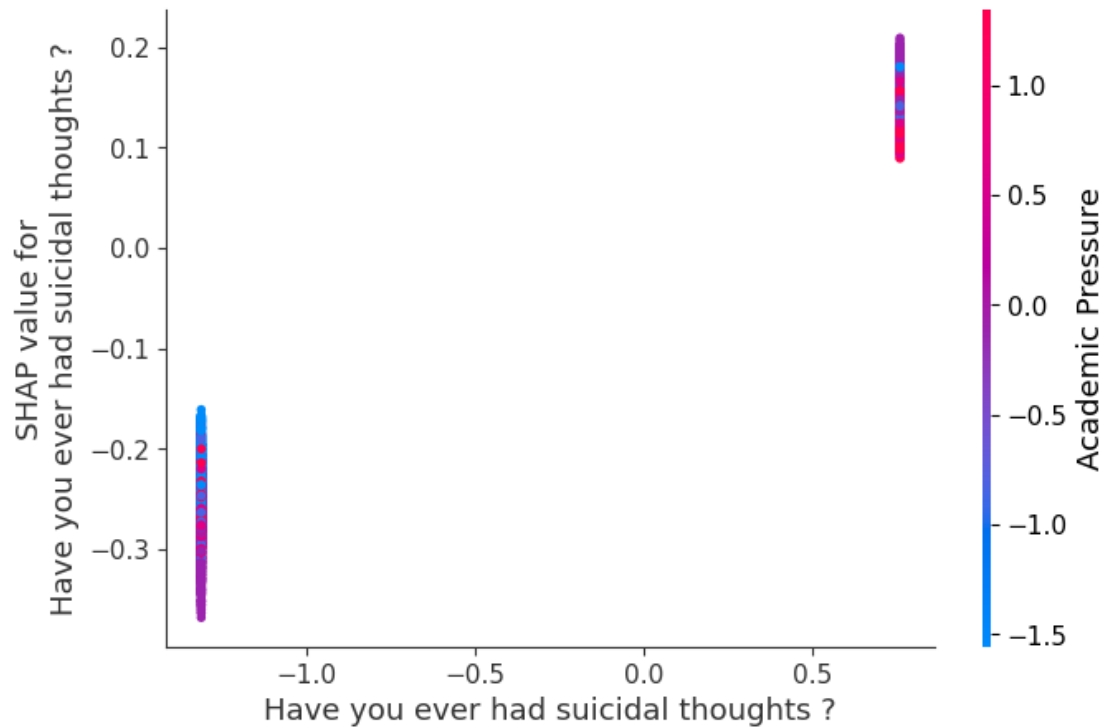
else:
    shap_values_pos = shap_values

shap.summary_plot(shap_values_pos, X_test_scaled, feature_names=features.
    ↪columns)

top_feature = features.columns[np.argmax(rf_grid.best_estimator_.
    ↪feature_importances_)]
shap.dependence_plot(top_feature, shap_values_pos, X_test_scaled,
    ↪feature_names=features.columns)

```





## 4 Statistical Tests

```
[34]: from scipy.stats import ttest_ind, chi2_contingency
```

```
[35]: # T-test: compare mean 'Work/Study Hours' for Depressed vs Not
if 'Work/Study Hours' in df.columns:
    group0 = df[df['Depression'] == 0]['Work/Study Hours']
    group1 = df[df['Depression'] == 1]['Work/Study Hours']
    t_stat, p_val = ttest_ind(group0, group1, nan_policy='omit')
    print(f"\nT-test for Work/Study Hours (Depressed vs Not): t={t_stat:.3f}, p={p_val:.4f}")
    if p_val < 0.05:
        print('Result: Significant difference.')
    else:
        print('Result: No significant difference.')
```

T-test for Work/Study Hours (Depressed vs Not): t=-35.620, p=0.0000  
Result: Significant difference.

```
[36]: # Chi-square: Gender vs Depression
if 'Gender' in df.columns:
    contingency = pd.crosstab(df['Gender'], df['Depression'])
```

```

chi2, p, _, _ = chi2_contingency(contingency)
print(f"\nChi-square for Gender vs Depression: chi2={chi2:.2f}, p={p:.4f}")
if p < 0.05:
    print('Result: Significant association.')
else:
    print('Result: No significant association.')

```

Chi-square for Gender vs Depression: chi2=0.08, p=0.7737  
Result: No significant association.

## 5 Model Export

```

[37]: # 14. Automated EDA Profiling Report (HTML)

# pip install ydata-profiling
from ydata_profiling import ProfileReport

profile = ProfileReport(df, title='Student Depression Dataset Profiling_
↳Report', explorative=True)
profile.to_file('student_depression_eda_report.html')
print('Automated EDA report saved as student_depression_eda_report.html')

```

<IPython.core.display.HTML object>

Summarize dataset: 0%| | 0/5 [00:00<?, ?it/s]

100%| | 18/18 [00:00<00:00, 76.86it/s]

Generate report structure: 0%| | 0/1 [00:00<?, ?it/s]

Render HTML: 0%| | 0/1 [00:00<?, ?it/s]

Export report to file: 0%| | 0/1 [00:00<?, ?it/s]

Automated EDA report saved as student\_depression\_eda\_report.html

```

[38]: import joblib
joblib.dump(rf_grid.best_estimator_, 'student_depression_rf_model.joblib')
print('Random Forest model saved as student_depression_rf_model.joblib')

```

Random Forest model saved as student\_depression\_rf\_model.joblib

```

[ ]: # 16. Data Dictionary & Group Summary

# Converts known numeric-looking columns to float
for col in ['Financial Stress']:
    if col in df.columns:
        df[col] = pd.to_numeric(df[col], errors='coerce')

# Numeric summary by Depression group

```

```

numeric_cols = df.select_dtypes(include=[np.number]).columns
group_summary = df.groupby(target_col)[numeric_cols].agg(['mean', 'std', 'count'])
print('\nSummary stats by Depression:\n', group_summary)
group_summary.to_csv('depression_group_summary.csv')
print('Group summary saved as depression_group_summary.csv')

# Data dictionary
print('\nDATA DICTIONARY:')
for col in df.columns:
    print(f"{col}: {df[col].dtype}, unique: {df[col].nunique()}, sample: {df[col].unique()[:3]}")

# Showing value counts for categoricals by group
cat_cols = df.select_dtypes(include='object').columns
for col in cat_cols:
    print(f"\nValue counts of '{col}' by {target_col}:")
    print(df.groupby(target_col)[col].value_counts())

```

Summary stats by Depression:

	id			Age		
	mean	std	count	mean	std	count
Depression						
0	70397.561089	40556.248313	11565	27.142412	4.943370	11565
1	70473.715536	40702.402805	16336	24.887733	4.658028	16336

	Academic Pressure			Work Pressure		
	mean	std	count	mean	std	count
Depression						
0	2.361608	1.252937	11565	0.000605		
1	3.693132	1.188834	16336	0.000306		

	Job Satisfaction			Work/Study Hours		
	count	mean	std	count	mean	std
Depression						
0	11565	6.237959	3.860943	11565		
1	16336	7.807603	3.450328	16336		

	Financial Stress			Depression		
	mean	std	count	mean	std	count
Depression						
0	2.518724	1.346952	11563	0.0	0.0	11565
1	3.579553	1.333337	16335	1.0	0.0	16336

[2 rows x 30 columns]

Group summary saved as depression\_group\_summary.csv

#### DATA DICTIONARY:

id: int64, unique: 27901, sample: [ 2 8 26]  
Gender: object, unique: 2, sample: ['Male' 'Female']  
Age: float64, unique: 34, sample: [33. 24. 31.]  
City: object, unique: 52, sample: ['Visakhapatnam' 'Bangalore' 'Srinagar']  
Profession: object, unique: 14, sample: ['Student' "'Civil Engineer'"  
'Architect']  
Academic Pressure: float64, unique: 6, sample: [5. 2. 3.]  
Work Pressure: float64, unique: 3, sample: [0. 5. 2.]  
CGPA: float64, unique: 332, sample: [8.97 5.9 7.03]  
Study Satisfaction: float64, unique: 6, sample: [2. 5. 3.]  
Job Satisfaction: float64, unique: 5, sample: [0. 3. 4.]  
Sleep Duration: object, unique: 5, sample: ["'5-6 hours'" "'Less than 5 hours'"  
'7-8 hours']  
Dietary Habits: object, unique: 4, sample: ['Healthy' 'Moderate' 'Unhealthy']  
Degree: object, unique: 28, sample: ['B.Pharm' 'BSc' 'BA']  
Have you ever had suicidal thoughts?: object, unique: 2, sample: ['Yes' 'No']  
Work/Study Hours: float64, unique: 13, sample: [3. 9. 4.]  
Financial Stress: float64, unique: 5, sample: [1. 2. 5.]  
Family History of Mental Illness: object, unique: 2, sample: ['No' 'Yes']  
Depression: int64, unique: 2, sample: [1 0]

#### Value counts of 'Gender' by Depression:

Depression	Gender	
0	Male	6432
	Female	5133
1	Male	9115
	Female	7221

Name: count, dtype: int64

#### Value counts of 'City' by Depression:

Depression	City	
0	Kalyan	636
	Srinagar	609
	Vasai-Virar	551
	Lucknow	514
	Agra	509
	...	
1	M.Com	1
	Mihir	1
	Mira	1
	Nalini	1
	Vaanya	1

Name: count, Length: 84, dtype: int64

#### Value counts of 'Profession' by Depression:

Depression	Profession
------------	------------

0	Student	11562
	'Digital Marketer'	1
	Architect	1
	Teacher	1
1	Student	16308
	Architect	7
	Teacher	5
	'Content Writer'	2
	'Digital Marketer'	2
	Chef	2
	Doctor	2
	Pharmacist	2
	'Civil Engineer'	1
	'Educational Consultant'	1
	'UX/UI Designer'	1
	Entrepreneur	1
	Lawyer	1
	Manager	1

Name: count, dtype: int64

Value counts of 'Sleep Duration' by Depression:

Depression	Sleep Duration	
0	'7-8 hours'	2975
	'More than 8 hours'	2966
	'Less than 5 hours'	2949
	'5-6 hours'	2666
	Others	9
1	'Less than 5 hours'	5361
	'7-8 hours'	4371
	'5-6 hours'	3517
	'More than 8 hours'	3078
	Others	9

Name: count, dtype: int64

Value counts of 'Dietary Habits' by Depression:

Depression	Dietary Habits	
0	Moderate	4363
	Healthy	4178
	Unhealthy	3020
	Others	4
1	Unhealthy	7297
	Moderate	5558
	Healthy	3473
	Others	8

Name: count, dtype: int64

Value counts of 'Degree' by Depression:

Depression	Degree
------------	--------



0	'Class 12'	1777
	B.Ed	846
	B.Com	653
	BCA	614
	B.Arch	607
	MSc	511
	M.Tech	501
	B.Tech	497
	MCA	485
	BHM	416
	M.Ed	406
	B.Pharm	382
	BSc	365
	M.Com	344
	LLB	315
	MBBS	292
	BBA	289
	BA	279
	BE	279
	MD	274
	M.Pharm	268
	MBA	259
	MA	254
	PhD	236
	LLM	223
	MHM	92
	ME	87
	Others	14
1	'Class 12'	4303
	B.Ed	1021
	B.Arch	871
	B.Com	853
	BCA	819
	MSc	679
	B.Tech	655
	MCA	559
	BSc	523
	M.Tech	521
	BHM	509
	B.Pharm	428
	M.Ed	415
	BBA	407
	MBBS	404
	M.Com	390
	LLB	356
	BE	334
	BA	321
	M.Pharm	314

MBA	303
MD	298
MA	290
PhD	286
LLM	259
MHM	99
ME	98
Others	21

Name: count, dtype: int64

Value counts of 'Have you ever had suicidal thoughts ?' by Depression:

Depression	Have you ever had suicidal thoughts ?	
0	No	7866
	Yes	3699
1	Yes	13957
	No	2379

Name: count, dtype: int64

Value counts of 'Family History of Mental Illness' by Depression:

Depression	Family History of Mental Illness	
0	No	6335
	Yes	5230
1	Yes	8273
	No	8063

Name: count, dtype: int64

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